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From Transition to Competition - Dynamic Efficiency Analysis of Polish Electricity Distribution Companies

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Abstract

In this paper we test the hypothesis that the economic transition toward a market economy increases the efficiency of firms. We study 32 Polish electricity distribution companies between 1997-2002, by applying common benchmarking methods to the panel: the nonparametric data envelopment analysis (DEA), the free disposal hull (FDH), and, as a parametric approach, the stochastic frontier analysis (SFA). We then measure and decompose productivity change with Malmquist indices. We find that the technical efficiency of the companies has indeed increased during the transition, while allocative efficiency has deteriorated. We also find significantly increasing returns to scale, suggesting that the regulatory authority should allow companies to merge into larger units.

Keywords: Efficiency analysis, electricity distribution, transition, econometric methods, Poland, DEA, SFA

JEL Classification: P31, L51, L43, C1

1 Introduction

One of the key concerns of the literature on economic transition in Eastern Europe is the link between economic reforms and productivity at the level of firms, sectors, and of national economies. In general, one expects that the move from central planning and state ownership toward market competition and more efficient corporate governance increases the productivity at all levels. Several studies confirm this hypothesis by applying productivity analysis such as data envelopment analysis (DEA) and stochastic frontier analysis (SFA). Thus, Halpern and Kőrösi (2001) show that in the Hungarian corporate sector increasing competition has lead to a gradual improvement in efficiency and a shift from decreasing to increasing returns to scale. Using an unbalanced panel of firms, Funke and Rahn (2002) show that the East German firms undergoing transition were significantly less efficient than firms in Western Germany. Similar studies using advanced quantitative methods include Brada, King and Ma (1997) on Czechoslovakia and Hungary; Jones, Klinedinst and Rock (1998) on Bulgaria; Piesse (2000) on Hungary; and Koop, Osiewalski and Steel (2000) on a comparison between the Polish and Western economies.

However, the past fifteen years have also taught us that not all expectations regarding the virtues of transition have materialized. This is particularly true in the capital-intensive and highly politicized infrastructure sectors, where reforms have sometimes been slow and painful (see EBRD, 1996, 2004, and Hirschhausen, 2002). In the last decade energy sector reform has been especially difficult because its mergers have often resulted in significant downsizing of employment and plant closures (see early evidence by Newbery, 1994 and Stern, 1994).

There have been few studies of restructuring's impact on the electric sector's productivity or on individual companies in the emerging internal energy markets in Europe. Kocenda and Cabelka (1999) studied the liberalization of the energy sector in the transition countries with respect to its effect on transition and growth. Filippini, Hrovatin and Zoric (2004) analyzed the efficiency of electricity distribution companies in Slovenia, using a stochastic frontier analysis. They found that Slovenian distribution companies were cost inefficient and that in a situation of increasing returns to scale most utilities did not achieve the minimum efficient scale. Cullmann, Apfelbeck and Hirschhausen (2006) provide a cross-country efficiency analysis of regional electricity distribution companies (RDCs) in four East European transition countries (Czech Republic, Slovakia, Hungary and Poland). Based on the cross-section data set for 2001 they find that the restructured Czech electricity distribution companies regularly obtained the highest efficiency scores; by contrast, the Polish had the lowest efficiency scores in the region, and were also found to be very heterogeneous amongst themselves.

In this paper, we provide a dynamic efficiency analysis of Polish regional electricity distribution companies during the transition period. Our aim is threefold: first, we want to validate the previous result that Polish RDCs could benefit from merging into larger units; second, we want to quantify how productivity evolves as the transition proceeds; third, we want to contribute to the current discussion in the literature on transition and productivity. We use a unique data set including technical data and cost and price data for six years (1997-2002). We apply a broad range of models to the Polish electricity distribution, such as cost efficiency models to evaluate allocative efficiency, and panel data analysis to estimate efficiency change over time.

This paper is structured in the following way: Section 2 describes the reform process of the energy sector in Poland since the beginning of economic transition, particularly the difficulties in restructuring this politically and socially sensitive sector. Section 3 introduces the data set, model specifications, and inputs and outputs used in the efficiency analysis. We then apply a series of traditional and some innovative approaches in nonparametric and parametric estimation: Section 4 presents the nonparametric approaches including data envelopment analysis (DEA), an ex ante descriptive statistical method for outlier detection, the stochastic DEA using the order-m efficiency estimates, and the free disposal hull (FDH) estimator. Section 5 presents results of the parametric approaches: output stochastic frontier analysis and different panel data models. We interpret and compare the results obtained. We find that overall transition did have a significant positive effect on technical efficiency whereas allocative efficiency decreased during that period. Section 6 offers our conclusions and suggestions for further research, and discusses several policy implications.

2 Electricity Restructuring Since Transition Began

Electricity sector-restructuring has proven to be one of the more difficult exercises in the process of economic transition and therefore has taken more effort and more time than initially expected. In socialist countries the electricity sector was assigned a prominent political and ideological role, (Lenin's "communism is Soviet power plus electrification"). Subsequently, reforms towards more market-oriented structures were challenging: the price system was changed from "social tariffs" to cost-covering prices; vertically integrated monopolies were unbundled while some portions became privatized; regulatory authorities were established; environmental standards and renewable-promotion schemes were implemented. Newbery (1994), Stern (1994) and Stern and Davis (1998) have provided evidence on the economic, regulatory and political challenges of restructuring the electricity sector; many of their observations are still valid. More recent evidence by EBRD (2004) and Hirschhausen and Zachmann (forthcoming) confirms that the electricity sector is still one of the unresolved legacies of transition in many countries.

Together with high voltage transport and low voltage distribution of electricity, regional electricity distribution retains many of the characteristics typical of a natural monopoly (subadditive cost function). This implies that contrary to electricity production and electricity retail, there can be no competition in electricity distribution. It also gives the electricity sector an important role both in socialist systems and in market economies. Electricity distribution is perhaps the most complicated element in restructuring, where industrial demand has collapsed at the same time residential use is rising.

Poland, by far the largest electricity producer and distributor among the East European transition countries, still has problems to resolve before it can completely reform its electricity sector. Its historical dependence on coal – a supply source that suffers from chronic over-employment, centralized bureaucratic structure, and a high degree of politicized decision-making – has weakened modernization efforts. For example, to preserve employment in several mines, Poland was forced to buy its own expensive coal. In socialist times, the electricity sector was organized by a Central Ministry which delegated operational powers to one electricity company in each of the 33 regions (voivody). The structure remained unchanged during the first decade of transition; by international comparison, 33 distribution companies is a large number for total sales of only about 90 TWh of electricity.

The country's capital stock also remained largely unchanged, and few investments occurred. To date, privatization of the distribution companies in Poland has been dragging on slowly with only 3 of the 33 companies being bought by (foreign) private investors. By international comparison, the Polish electricity sector has lost attractiveness vis-a-vis more active transition countries, such as the Czech Republic and Hungary. Recently, however, the reform process has picked up speed, with attempts to merge the existing regional structures into seven large distribution companies and therefore to benefit from the assumed economies of scale. This consolidation plan also includes the creation of a few large holding companies for electricity generation ("national champions"). In the first round of consolidation, 14 regional companies were created out of the initial 33 distributors. From an economic perspective, such concentration is justified if the size of the units can be shown to be too small. This is a major concern of this paper and the following quantitative analysis.

3 Data, Variables, and Model Specifications

3.1 Data

Our analysis is based on a panel data set for 32 Polish regional distribution companies for the period between 1997 and 2002.[4] Both technical and cost

[4]Data for one company (Gornoslaski Zaklad Elektroenergetyczny SA) was completely missing.

data is available from the utilities' annual reports from 1997 onwards; before that year, companies were not obliged to report this data systematically. In 2003, the merger process set in, and it became more difficult to compare the companies.

The electricity distribution companies operate under very similar technical and institutional conditions. As natural monopolies, their tariff setting is subject to supervision by the national Polish regulatory authority. Table 1 provides a summary of the main data of the companies. The size, in terms of km^2 distribution area, is quite similar among the 32 companies.[5] On the other hand, there are considerable differences in consumer density, in particular between the more densely settled regions in the Center and the South of the country and the less densely settled regions in the North and East.

Partial productivity indicators vary somewhat among the 32 companies. The average labor productivity has increased from 1765 Mwh per employee in 1997 to 2152 in 2002. The firms feature different labor productivity, such as Zamojska Korporacja Energetyczna SA (1097 MWh per employee) and Zaklad Energetyczny Plock SA (12199 MWh per employee). This is partly due to variations in outsourcing (for which no data is available).[6]

[5] In that respect, the Polish distribution companies are more homogeneous than for instance in neighboring Germany. The two exceptions which are smaller than the average are STOEN, the Warsaw distribution company, and Lodzki Zaklad Energetyczny SA.

[6] We reported in Table 1 for labor and labor productivity on the one hand the total number of employees within the companies, where no large changes were detected and on the other hand the maximum of labor productivity for the companies in a whole. From 1999 onwards the maximal labor productivity is always achieved by just one company

Another partial performance measure, the number of customers per employee, also increased on average from 270 in 1997 to 364 in 2002. Capital productivity is approximated by the ratio of electricity sold in Mwh divided by network length. The average capital productivity is rather constant over the period, ranging from 101 Mwh per km network to 106 Mwh per km of network. This indicates that input factor adaptation largely relies on labor, but that there is some flexibility regarding the capital input ($\sim$ network length) as well.

3.2 Variable definition

The available data allows for an analysis of both the technical and the cost efficiency. There exists a wide variety of parametric and nonparametric approaches to estimate the production frontier and to derive the efficiency of the individual firms.[7] For estimating the technical efficiency, we use a traditional model which has been applied for similar sector studies (Hirschhausen et al., forthcoming, and Cullmann, et al., 2006): labor and capital are used as inputs, electricity distribution and the number of customers are the output.[8]

Labor input is estimated by the number of workers. The descriptive statistics

(Zaklad Energetyczny Plock SA). This company outsourced some parts of their services because the number of employees within this company decreased significantly from one year to another (from 1999 onwards). That is the reason why the maximum value increased by three times in one year whereas no large changes were detected in the number of employees.

[7]For a survey, see Jamasb and Pollit (2001).

[8]Estache et al. (2004), include e.g. transformer capacity as a further capital input. This was not possible for the Polish distribution companies because of data availability.

(Table 1) show that total employment in the Polish electricity distribution has decreased over the years. Capital input is approximated by the length of the existing electricity cables. We differentiate between voltage levels (high, medium, and low) by introducing a cost factor for each type of line.[9]

We use the amount of electricity distributed to end users (units sold) and the total number of customers as output variables. The amount of electricity distributed somewhat declined from 89.2 GWh (1997) to 86.7 GWh (2002); this trend is representative for the transition period, as rising electricity prices and increased energy efficiency dampen consumption. The number of customers increased mainly due to the rising number of residential households. On the output side, we also include an inverse density index (settled area in km^2 per inhabitant) to account for the structural differences: this index (IDI) favors the efficiency scores of less densely inhabited regions.

Our cost model includes total cost (Totex), capital costs, and labor costs. Totex and labor costs are available for all companies in Polish Zloty (Plz). The average wages and the input factor price for labor, are calculated as the ratio of labor expenditures divided by the number of employees.[10] Following Filippini, et al. (2004), we define capital costs as the difference between total cost and labor costs. The capital stock is approximated by network

[9] The factors are = 1, 1,6, and 5 for low, medium and high voltage respectively. They are adopted from Verband Deutscher Elektrizitätswirtschaft's (2001) estimates for Germany's electricity distribution.

[10] In Poland, almost all companies apply public sector wages bargained collectively at the national level; thus there are no substantial regional labor cost differences. As a result the average salary varies across companies mainly because of the age and education structure of employees.

length. We can thus derive the "price" of capital as the ratio of (residual) capital cost and the capital stock ($\sim$ network length).

All input prices and costs were deflated by means of the price index of sold production of industry (1995=100) available from the statistical information center in Poland. Average costs varied significantly between the companies with a difference of up to 50 Plz/MWh. Although there were major labor reductions during our study period, total labor costs increased because of rising wages. Capital costs and output prices also rose.

3.3 Model specification

Applied empirical work on efficiency and productivity measurement of individual firms is always confronted with the high sensitivity of the results to the different approaches and the variation in firm's input and output parameters to describe the production process of the industry (see e.g Zhu, J., 2003). Therefore, with the aim of reflecting a significant and robust image of the economic operations, this study discusses, applies and compares a variety of approaches. In essence, choices must be made using the following criteria: i) nonparametric vs. parametric approaches; ii) technical efficiency models vs. allocative efficiency models; iii) deterministic vs. stochastic approaches (see Coelli et al., 2005, for a survey).

Based on the available data and our own modeling experience, we chose the following models: a DEA Model 1 which uses the traditional choice of technical efficiency analysis: the inputs are the number of employees (labor), and the length of the electricity grid (capital); the outputs are total sales (in GWh) and the number of customers. In the extended version of the model (DEA Model 2), we include a structural variable to account for structural differences among regions: the inverse density index (IDI, measured in km^2 per inhabitant). To obtain robust and reliable results, we then estimate the extended DEA Model 2 also by the FDH-approach (free disposal hull, FDH Model 1) and the stochastic DEA, the so-called order-m Estimator (Order-m Model 1). For the stochastic approach to technical efficiency analysis, the SFA Model 1 uses the basic set of two inputs and two outputs, to which we add the structural inverse density index (IDI) in SFA Model 2. We apply two different panel data specifications, Battese and Coelli (1992), called SFA Model 1, and Battese and Coelli (1995), called SFA Model 2, which we discuss in Section 5.1. Table 2 summarizes the models for estimating technical efficiency.

With regard to estimating allocative efficiency, we estimated nonparametric approaches and parametric cost functions (see Table 3): DEA Model 3 uses total cost as a dependent variable, whereas DEA Model 4 uses the physical output "electricity sold" (in MWh) and the number of customers. DEA Model 5 uses total costs as input, and the amount of electricity sold and the number of customers as output. SFA Model 3 defines the total costs as the dependent variable and both outputs (electricity sold and number of customers) and the input factor prices as regressors. In addition we apply fixed and random effects panel models developed by Greene (2005). In SFA Model 4 and 5 we define the input as the sum of the monetized input factors, the total costs, and the aggregated output index as the dependent variable.

4 Nonparametric Approaches and Results

4.1 Basic DEA, FDH, and stochastic DEA

We apply common nonparametric estimators for efficiency measurement such as the data envelopment analysis (DEA) and the free disposal hull (FDH) estimator, proposed by Deprins et al. (1984). In addition we also apply recently developed approaches, such as the stochastic DEA, the so-called order-m estimator, proposed by Cazals, Florens and Simar (2002). The idea of estimating production efficiency scores in a deterministic non-parametric framework was originally proposed by Farrell (1957) who defines a measure of firm efficiency relative to a given technology (the production frontier) which can be estimated by envelopment techniques, such as DEA and FDH. DEA involves the use of linear programming methods to construct a piecewise linear surface or frontier over the data and measures the efficiency for a given unit relative to the boundary of the convex hull of $X = \{(x_i, y_i), i = 1...n\}$, where x_i defines the input vector and y_i the output vector of the ith out of n firms.

$$\widehat{\theta_k} = \min\{\theta | y_k \leq \sum_{i=1}^{n} \gamma_i \; y_i; \theta \; x_k \geq \sum_{i=1}^{n} \gamma_i \; x_i; \theta > 0; \gamma_i \geq 0, i = 1, ...n\} \quad (1)$$

Following Simar and Wilson (1998), $\widehat{\theta_k}$ measures the radial distance between the observation x_k, y_k and the point on the frontier characterized by the level of inputs that should be reached to be efficient. A value of $\theta_k = 1$ indicates that a firm is fully efficient and thus is located on the efficiency frontier. γ_i are the weights attached to different firms' inputs and outputs.

Efficiency scores can be obtained either within a constant returns to scale (CRS) approach or a less restrictive variable returns to scale (VRS) approach. The VRS approach compares companies only within similar sample sizes; this approach is appropriate if the utilities are not free to choose or adapt their size. With respect to the DEA analysis we emphasize the constant returns to scale approach (CRS), because we expect the Polish RDCs to adapt towards an optimal firm size. Calculations can be done using an input-orientation or an output-orientation. Traditionally, efficiency analysis in the electricity sector assumes the output fixed in a market with the legal duty to serve all customers in a predefined service territory.

The DEA estimates may depend heavily on the assumption that the production frontier is convex. The FDH estimator, in contrast, relaxes the assumption of convexity. Cazals et al. (2002) propose the nonparametric order-m estimator as an alternative, which is based on the expected minimum input frontier. This type of estimator is more robust since it permits noise in input measures, and consequently individual observations including extreme outliers have much less influence on the efficiency frontier.[11]

4.2 Empirical results: technical efficiency

In DEA Model 1 the Polish companies achieve an average technical efficiency of 0.59 under a CRS assumption.[12] When applying the less constraining VRS approach, the Polish RDCs considerably gain in efficiency, reaching an average efficiency level of 0.75. Figure 1 shows the differences of DEA Model 1 under a CRS assumption and DEA Model 1 under a VRS assumption.[13] In comparison to other Central European new EU member states, Poland is relatively large but it has got overproportionally many distribution companies. The low technical CRS efficiency scores combined with a notable difference in the VRS scores indicate that the Polish electricity distribution companies are "too small to be efficient".[14] We postulate that their inefficiency chiefly originates in their size.

Including the inverse density index in DEA Model 2 changes the rank of the individual firms. Companies which operate in a less favourable environment, particularly the smaller companies, significantly gain efficiency in all years.

[11]For details see Cazals et al. (2002) and Wheelock and Wilson (2003).

[12]The correlation analysis of the individual efficiency estimates for each year ranges around 0.9, implying that there is no significant change between the different years at the company level.

[13]In the following graphs the firms are ordered by size, defined in our analysis by electricity sold in Mwh, beginning with the largest company in each year at the left.

[14]In all years, 50 per cent of the larger companies are on average more efficient than the smaller ones, which also indicate that there are increasing returns to scale.

The average efficiency increases to 0.72 under CRS and 0.79 under VRS.

In both models we observe that the average efficiency increases slightly over the years.[15] Our result can be confirmed by Malmquist indices which measure the change of total factor productivity for a particular firm between two periods.[16] The empirical results indicate a technical change of 1.026 on average during the observation period. This implies that the technical efficiency increase found in our DEA Model 1 and DEA Model 2 results from technical progress.

In addition, we note the sensitivity of the results from a different set of production assumptions by estimating the technical efficiencies using the FDH Model 1. Only 13 enterprises out of our sample are not classified as fully efficient. We also note that in every period the same utilities are classified as inefficient. All of the firms classified as inefficient are medium-sized or smaller when size is defined as the annual amount of electricity sold. Thus, the inefficiency of these companies can be seen as robust.

When enlarging our analysis to the stochastic nonparametric approach, the order-m estimation. We find that technical efficiency also increases dur-

[15] In DEA Model 1 from 0.56 to 0.59 under CRS, and 0.71 to 0.75 under VRS, and in DEA Model 2 from 69.7 to 73.1 under CRS and from 77.3 to 80.2 under VRS.

[16] The index is constructed by measuring the radial distance of the observed output and input vectors in periods s and t relative to the reference technologies Ss and St. By means of the Malmquist indices one can decompose efficiency change into technical, efficiency and total factor productivity components (for more details see Coelli, 2005, p. 67).

ing the observation period from 0.93 to 0.97. Thus the results from the DEA Models 1 and 2 can be confirmed.

4.3 Empirical results: allocative efficiency

We now provide an overall economic efficiency measure, the allocative efficiency of the firms. In DEA Model 3 we estimated the relative cost efficiency of the firms by relating the inputs to the respective factor prices. We find that while the technical efficiency increases, from 0.76 in 1997 to 0.81 in 2002, the allocative efficiency decreases moderately, from 0.87 in 1997 to 0.84 in 2002. This implies that the cost efficiency or the overall efficiency of the firms, calculated as the product of technical and allocative efficiency, remains at a similar level. Thus we observe two trends: first, over the years, the utilities learned to improve the technical aspect of the production process; second, they were unable allocate the inputs more efficiently. This result can be confirmed by using DEA Model 5, where we include the total costs as input instead of the physical input factors. Again we note that the companies failed to utilize the input factors more cost effectively.

Looking at individual firms we note that across all model specifications, STOEN was the most efficient. This can be explained by its customer structure, both with regard to density and to specific electricity consumption patterns; there is a high degree of industrial demand, for example. The results remain valid when we compensate other regions for their structural disadvantage, by using the inverse density index. Other metropolitan distributors, like Lodz, Krakow, or Wroclaw do not achieve the same technical efficiency, but their efficiency scores remain above average.

5 Parametric Approaches and Results

5.1 Stochastic frontier model and panel data models

The stochastic frontier approaches[17] provide a parametrization of the input-output relationship. Contrary to the ordinary least squares (OLS), the stochastic frontier model decomposes the residuals into a symmetric component ν_i representing statistical noise, and an asymmetric component representing inefficiency u_i.[18] Referring to the translog functional form yields the stochastic frontier production function in the following form

$$\ln y_i = \beta_0 + \sum_{n=1}^{N} \beta_n \ln x_{ni} + \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{N} \beta_{nmi} \ln x_{ni} \ln x_{mi} + \nu_i - u_i \quad (2)$$

where i is the index for firm i.

[17]The theory of stochastic frontier production functions was originally proposed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977).

[18]See also Coelli (2005, p. 243). For the noise components ν_i it is assumed that they are independently and identically distributed normal random variables with zero mean and variance σ_v^2 $\nu_i \sim iidN(0, \sigma_v^2)$. Alternatives for the distributional specifications of the u_is as well as the likelihood functions for the different models are summarized in Kumbhakar and Lovell (2000). The above measures of technical efficiency rely on the value of the unobservable u_i being predicted (see Coelli, 2005, p. 8).

We apply two types of panel analysis: the first is based on Battese and Coelli (1992, 1995) and the second based on Greene (2005), respectively. Battese and Coelli (1992) proposed a random effects model with a varying technical inefficiency over time as follows.

$$u_i t = f(t) \cdot u_i \tag{3}$$

where

$$f(t) = \exp[\eta(t - T)] \tag{4}$$

η is an unknown parameters to be estimated.

The Battese and Coelli (1995) specification accounts explicitly for environmental non-stochastic factors such as the inverse density. The inefficiency effects u_i are expressed as an explicit function of a vector of firm specific variables and a random error (see Coelli, 1996, p. 5)

$$u_i \sim N^+(z'_{it}\gamma, \sigma_u^2) \tag{5}$$

where z_{it} is a vector of environmental variables which may influence the inefficiency effects u_i, and γ is a vector of parameters to be estimated. The other variables are defined as above.

The major shortcoming of the above specified and estimated panel data models is that any unobserved time-invariant, firm-specific heterogeneity is considered as inefficiency. To overcome this problem, we estimated in a second step the fixed and random effects models derived by Greene (2005), who extended the stochastic frontier model in its original form to panel data models by adding a fixed or random effect in the model.[19] The true fixed effects model can be expressed by

$$y_{it} = \alpha_i + x'_{it}\beta + v_{it} - u_{it} \tag{6}$$

In fact, one can interpret the model as if a full set of firm dummy variables were added to the stochastic frontier model capturing the unmeasured heterogeneity directly in the production function, (Greene, 2005). The true random effects frontier model can be expressed by

$$y_{it} = (\alpha + w_i) + x'_{it}\beta + v_{it} - u_{it} \tag{7}$$

where w_i, a random (across firms) constant term, represents the cross section heterogeneity.

[19]The two are called the true fixed effects model and the true random effects model, respectively. The two sets of maximum likelihood estimates as well as the inefficiency predictions were obtained using LIMDEP (Greene, 2002).

5.2 Empirical results: structural variable, technical change and cost efficiency

The lower parts of Tables 2 and 3, respectively, provide the concrete specification of the parametric models that we use. For the SFA models the outputs were aggregated[20] to create a joint index for total sales and the number of customers. We calculated the predicted technical efficiency according to Coelli (1996), assuming a truncated normal distribution for the technical inefficiencies. In a first step, in order to compare the SFA results to the pooled DEA, we ran SFA Models 1 and 2 without and with technical change. Therefore in the first model specifications the results indicate the average technical efficiency of the firms across the observation period. The results of this approach lead to the same trend observed in the nonparametric DEA Model 1: the average efficiency score of the 50 per cent largest enterprises is 0.74, whereas it is only 0.56 for the lower half of the sample. The SFA Model 2, including the structural variable, indicates that the inverse density index has a significant influence that the larger utilities are on average more efficient. In both stochastic frontier specifications we find evidence that STOEN is relatively more efficient than the other companies.

We conduct model variation for both SFA Model 1 and SFA Model 2, first assuming a constant trend, and then extending the analysis by allowing

[20] For the SFA run the outputs were logged and weighted fifty percent each.

the technological change to increase or decrease with time. The estimates of the technical change parameters indicate a technological progress which decreases over the sample period since the sign of the squared time trend is negative. More precisely, we estimate that output increased at a ratio of approximately 2.4 per cent per annum due to technological change. We can summarize that the SFA results are similar to the DEA results. We observe some technological change in the electricity distribution industry.

The stochastic cost frontier specification (SFA Model 3) identifies the minimum costs at a given output level, the input factor prices, and the existing production technology. The specification of the cost frontier is similar to Farsi and Filippini (2004).[21] Linear homogeneity in input prices is imposed by dividing the monetized values by the price of the capital. We observe an increase in the annual average cost inefficiency over the years from 30 per cent in 1997 to 41 per cent in 2002. From 1997-2002 50 per cent of the largest companies operated on the same cost efficiency level as the smaller utilities. This changed in the last two years of our observation panel when the small utilities become slightly more inefficient than the larger ones.

[21] A Cobb Douglas functional form has been adapted, because we want to avoid the risk of multicollinearity among second order terms due to the large number of parameters in a translog model, and the strong correlation between output characteristics, (see Filippini 2004 p.13).

5.3 Distinguishing firm specific heterogeneity from inefficiency

We now turn to the estimation results of SFA Models 4 and 5 where we define total costs as regressor, so as an approximate for labor and capital input. In both models the average efficiency decreases from 1997-2002 (see Figure 3). This effect is stronger in the last two years. In 2002 the average efficiency dropped almost 3 per cent in the fixed effects specification and 4 per cent in the random effects specification, respectively. The overall trend exhibited in the other models remains valid: there is an increase in the cost inefficient use of the input factors in the Polish distributors. Factors that may account for the inefficiency include a decreasing amount of electricity sold to end users in the last two years combined with higher costs induced by new customers and new interconnections on the grid.

In comparison to the previous SFA Models 1-3 the inefficiency estimates obtained from the fixed effects and the random parameter specification are 30 per cent lower on average. This result is consistent with the theory, since the models now distinguish heterogeneity from inefficiency, and thus allocate less of the error term to the inefficiency term. We thus confirm recent studies such as Farsi et al. (2006), suggesting that the inefficiency estimates are sensitive to the specification of unobserved firm specific heterogeneity. The inefficiency scores obtained from the traditional specifications (including unobserved environmental factors) most likely overstate the inefficiency of the Polish companies.

5.4 Consistency of results

Bauer et al. (1998) propose a set of consistency conditions for frontier efficiency measures that we apply. They point out that the efficiency estimates should be consistent in their efficiency levels, rankings and identification of best and worst firms, consistent over time and with competitive conditions in the market and consistent with nonfrontier measures of performance. To analyze the consistency of our different models we apply two different conditions outlined in Bauer et al. (1998): 1) we compare the efficiency distributions with each other, and 2) we look at the rank order correlations of the efficiency distributions.

The distributional characteristics of the efficiency scores across our different model specifications are reported in Table 4. The nonparametric models feature a mean of 0.718 and the parametric models a mean of 0.705, thus very similar values within the different frontier concepts. We notice that the average standard deviation from the parametric models (0.089) is significantly lower than for the nonparametric models (0.141). The mean correlation across all specification is about 0.42. This indicates that the estimates of the levels of technical and cost efficiency of the parametric and nonparametric frontier methods, as outlined in Bauer et al. (1998) feature some differences. That is the reason why we focused more on general trends and their consistency across specification and time rather than on the interpretation of individual efficiency scores.

We now turn to the rank order correlation of the efficiency distributions to look whether different methods will generate similar rankings of the distribution utilities. As Bauer et al. (1998) pointed out identifying the rough ordering of which utilities are more efficient than others is important for regulatory policy decisions. If different frontier approaches lead to different rankings, then policy conclusions may be fragile and depend highly on the choice of the method. Table 5 shows the Spearman rank-order correlation coefficients for selected models.[22] The average rank correlation among the nonparametric models was 0.52, whereas the correlation among the selected parametric models was only about 0.2. Thus the data suggests that the parametric techniques with the different specifications and distributional assumptions give only weakly consistent rankings with each other. When we compare the selected nonparametric with the parametric ones, we obtain an average Spearman rank-order correlation coefficient of 0.25. Thus we conclude that when looking at the firm level, the different approaches do not lead to rank the utilities in the same order. Therefore, as outlined above, the interpretation of the results should be limited to the general trends with regard to the size of the companies and the changes within time, rather to conclude detailed regulatory policy conclusion at the firm level. More detailed and sophisticated models would need to be applied in order to conduct an extensive firm level analysis.

[22] We based the rank of the firms for each approach on the average efficiency value over the entire observation period of six years.

6 Conclusions and Outlook

In this paper we have analyzed the efficiency of electricity distribution companies in Poland - one of the more advanced transition countries that has recently joined the EU. We have observed that the reform process in this sector is heavily influenced by the legacy of socialist energy policies and by attempts to modernize the sector in the wake of EU-accession. We take as the point of inception the results from Cullmann et al. (2006) of a rather low efficiency of Polish companies, and a large dispersion within the sample. The extensive dataset assembled for the current study contains technical, cost and price data for 1997-2002, thus allowing for a range of model specifications and simulation analyses. We also conducted a dynamic analysis to reveal the efficiency change throughout the time period and verified if transition enhances technical and allocative efficiency.

We discovered that while technical efficiency increased during the transition period for the distribution companies, allocative efficiency did not. This indicates that the companies were able to adapt their physical ratio of outputs to inputs, i.e. to deliver the same level of services using less inputs. On the other hand, the price developments during the transition were not properly accounted for. We also found that input factors were not allocated in a cost-efficient way.

We demonstrated that there were marked differences between the efficiency scores of larger companies in comparison to the smaller ones (size being defined by the amount of electricity sold). The results indicate that the smaller utilities are on average less efficient, largely due to scale inefficiency. This effect is neutralized when we introduce the inverse density index. The lack of scale efficiency does not change over our observation period. It can be concluded that the process of merging 33 distribution utilities into a handful of larger groups is an appropriate policy. The distribution company STOEN, which serves Warsaw, regularly achieves the highest efficiency scores; this can be explained by the favorable structural condition that the company focus.

From a methodological perspective, we find that the results derived by non-parametric and parametric analysis are consistent and largely robust with respect to the model specification. Correlation matrices generally yield relatively high values, whereas rank-order correlations are less robust.

Further research should focus on the effects of the merger effort that began in 2003 and the implications for the efficiency scores. It seems worth while to conduct a dynamic comparative analysis with neighboring transition countries, such as the Czech Republic, Slovakia and Hungary and with traditional West European countries such as Germany or France.

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Table 1: Descriptive Statistics

Year		Network Length in km	Labor	Customers	Electricity Sold in MWh	Inverse Density Index sqkm/inha.	Labor Productivity (MWh/) employees)	Capital Productivity (MwH/km)	Customers/ Employee
1997	sum	946736	49782	13850514	89255000				
	av	29585	1555	432828	2789218	0,0092	1764,7	106,3	270,4
	med	24174	1646	418780	2686500	0,0090	1638,8	90,3	264,5
	min	13179	779	156503	794000	0,0003	947,5	39,0	186,8
	max	57675	2749	854928	5979000	0,0177	3338,4	320,2	453,8
	std	14169	500	190873	1293245	0,0046	560,7	61,6	58,4
1998	sum	946736	48178	13950957	88622872				
	av	29585	1505	435967	2769464	0,0092	1816,9	105,4	282,7
	med	24174	1616	421229	2716665	0,0090	1657,9	91,7	275,2
	min	13179	784	158040	801810	0,0003	987,5	39,1	194,6
	max	57675	2725	862110	5643915	0,0177	3267,1	302,2	492,8
	std	14169	504	193014	1268507	0,0046	561,0	60,0	63,9
1999	sum	956034	46468	14051383	86210740				
	av	29876	1452	439105	2694085	0,0092	2072,1	102,1	339,3
	med	24174	1601	423678	2551200	0,0090	1636,2	87,8	281,8
	min	12860	177	159577	809620	0,0003	849,4	39,2	202,0
	max	64602	2701	869291	5308830	0,0177	10527,3	285,4	1915,5
	std	14888	539	195183	1283574	0,0046	1661,8	60,9	295,5
2000	sum	958212	45776	14050988	89470372				
	av	29944	1430	439093	2795949	0,0092	2226,1	106,7	352,1
	med	24174	1589	423728	2680172	0,0090	1740,7	90,6	288,6
	min	10146	163	159577	838043	0,0003	1098,0	38,5	195,1
	max	65104	2711	869291	5603370	0,0177	12199,6	300,4	2080,0
	std	15108	560	195197	1316623	0,0046	1908,7	62,9	322,7
2001	sum	962620	45894	14276360	87912990				
	av	30081	1434	446136	2747280	0,0092	2119,5	104,4	354,1
	med	24481	1587	428286	2523575	0,0090	1638,1	90,4	290,2
	min	10180	163	163576	818240	0,0003	1056,7	37,4	200,9
	max	66134	2718	885631	5627910	0,0177	10179,3	305,7	2108,8
	std	15240	549	200772	1327812	0,0046	1582,8	62,3	327,5
2002	sum	966510	45602	14369829	86639108				
	av	30203	1425	449057	2707472	0,0092	2152,3	101,4	364,5
	med	24511	1570	428826	2545220	0,0090	1620,3	90,9	293,9
	min	10191	149	164489	820248	0,0003	1024,8	36,3	200,7
	max	66794	2763	890650	5677214	0,0177	11780,0	305,7	2314,9
	std	15278	550	203237	1296262	0,0046	1847,1	57,6	362,8

Table 2: Model Specification - Technical Efficiency

Model	Input		Output		
	Employees	Network Length	Electricity sold	Customers	Inverse Density Index
I) Nonparametric Deterministic					
DEA Model 1	•	•	•	•	
DEA Model 2	•	•	•	•	•
FDH Model 1	•	•	•	•	•
Stochastic					
Order-m Model 1	•	•	•	•	•
II) Parametric Stochastic					
SFA Model 1 (BC 1992)	•	•	•	•	
SFA Model 2 (BC 1995)	•	•	•	•	•

Table 3: Model Specification - Allocative Efficiency

Model	Input		Input Factor Prices		Output			Input/ Output
	Employees	Network Length	Labor Price	Capital Price	Electricity sold	Customers	IDI	Total Costs
I) Nonparametric Deterministic								
DEA Model 3	•	•	•	•				•
DEA Model 4	•	•	•	•	•	•		
DEA Model 5					•	•		•
II) Parametric Stochastic								
SFA Model 3 (BC 1992)			•	•	•	•	•	•
SFA Model 4 (Fixed Effects)					•	•		•
SFA Model 5 (Random Coefficient)					•	•		•

Table 4: Distributional Characteristics of the Efficiency Scores

	DEA Model 1 CRS	DEA Model 1 VRS	DEA Model 2 CRS	DEA Model 2 VRS	DEA Model 3 TE	DEA Model 3 AE	DEA Model 3 CE	DEA Model 4 TE
mean	0.585	0.745	0.722	0.811	0.681	0.766	0.532	0.751
med	0.544	0.717	0.691	0.779	0.658	0.749	0.511	0.725
min	0.406	0.503	0.518	0.623	0.407	0.547	0.25	0.508
max	0.96	0.978	1.000	1.000	0.976	0.999	0.907	0.983
std dev.	0.146	0.156	0.149	0.12	0.173	0.129	0.198	0.152

	DEA Model 4 AE	DEA Model 4 CE	SFA Model 1 (BC 1992)	SFA Model 2 (BC 1995)	SFA Model 3 (BC 1992)	SFA Model 4 FE	SFA Model 5 RE
mean	0.764	0.587	0.597	0.472	0.757	0.908	0.88
med	0.747	0.574	0.581	0.454	0.723	0.909	0.881
min	0.527	0.307	0.419	0.278	0.529	0.893	0.813
max	0.998	0.98	0.973	0.942	0.976	0.912	0.95
std dev.	0.139	0.208	0.119	0.126	0.123	0.004	0.035

Table 5: Spearman Rank-order Correlation Coefficients for Selected Models

	DEA Model 1 CRS	DEA Model 1 VRS	DEA Model 2 CRS	DEA Model 3 TE	SFA Model 1 (BC 1992)	SFA Model 2 (BC 1995)	SFA Model 3 (BC 1992)	SFA Model 4 FE	SFA Model 5 RE
DEA Model 1 CRS	1.000	0.329	0.211	0.1	0.748	0.753	0.183	-0.165	-0.187
DEA Model 1 VRS		1.000	0.88	0.858	0.159	0.361	0.49	-0.086	0.262
DEA Model 2 CRS			1.000	0.732	0.006	0.137	0.446	0.107	0.307
DEA Model 3 TE				1.000	0.048	0.344	0.544	-0.097	0.247
SFA Model 1 (BC 1992)					1.000	0.899	0.262	-0.195	-0.143
SFA Model 2 (BC 1995)						1.000	0.467	-0.236	-0.051
SFA Model 3 (BC 1992)							1.000	-0.005	0.301
SFA Model 4 FE								1.000	-0.027
SFA Model 5 RC									1.000

Figure 1: Difference Results DEA Model 1 (VRS - CRS)

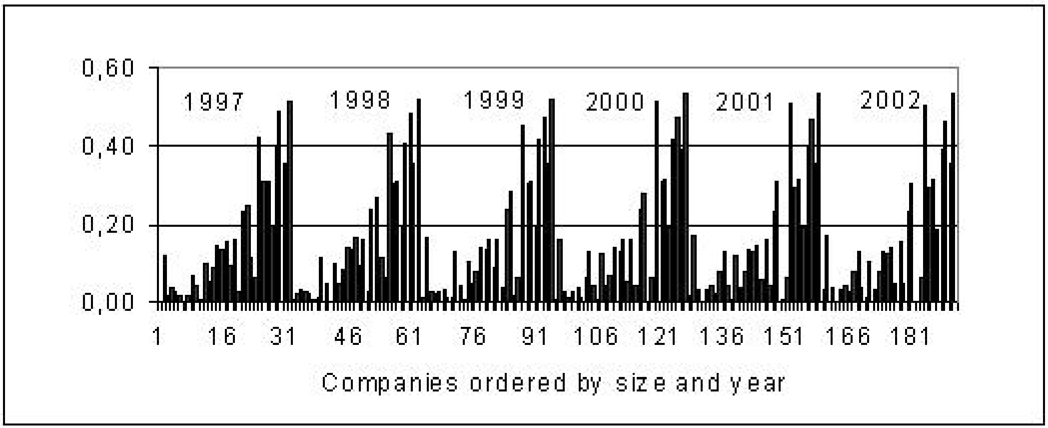

Figure 2: Average Annual Efficiency - Fixed and Random Effects Model